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Application of Polynomial Regression Method in Non-invasive Measurement of Blood Sugar, Cholesterol, and Non-invasive Uric Acid Based on IoT

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Abstract

Early disease avoidance depends much on health monitoring. However, the general examination methods still used today are invasive, namely, using a syringe to take blood samples. Many do not undergo routine examinations because this method is uncomfortable and expensive. In this study, the MAX30105 optical sensor is used as a non-invasive measuring device that can read the reflection of infrared light from the fingertip. After that, the second-order polynomial regression method is used to process the sensor data and determine the blood sugar, cholesterol, and uric acid levels. Using calibration data, this tool will change the reflected light signal into numbers for these three substances. The quantitative experimental method was conducted on 15 participants, The quantitative experimental method was carried out on 15 participants, the test results showed that blood sugar levels reached 91.50%, cholesterol levels reached 86.07%, and uric acid levels reached 89.33%. Real-time data transmission is carried out through the Adafruit IO platform, which was chosen for its accessibility and ease of integration. At the same time, a mobile application was developed using MIT App Inventor for user-friendly health data visualization. A preliminary Quality of Service (QoS) assessment showed an average data latency of 500–700 ms and a 97% transmission success rate via Wi-Fi. These results indicate that this device is reasonably practical and comfortable. However, several factors, such as skin thickness, finger position, and skin cleanliness, can affect the accuracy of the measurement results. Therefore, this tool cannot yet replace regular medical standards.

Keywords: Internet of Things (IoT), MAX30105 Sensor, Non-invasive, Polynomial Regression.

1. Introduction

Lifestyle changes have made noncommunicable diseases (NCDs) a major global health burden. According the World Health Organization (WHO) fact sheet from December 23, 2024, says that NCDs caused at least 43 million fatalities in 2021, which is 75% of all deaths that were not caused by a pandemic. Heart disease, cancer, chronic respiratory disorders, and diabetes are some of the most common reasons. These conditions are often driven by metabolic disorders that can damage vital organs such as the heart and blood vessels [1].

One of the major lifestyle factors influencing metabolic health is dietary habits. It has been shown that eating too many added sugars raises the risk of obesity, type 2 diabetes, and coronary heart disease [2]. Not getting enough sleep makes these risks even worse, sleeping less than 6 hours per night increases the risk of cardiovascular mortality by up to 40% compared to sleeping 7–8 hours (HR 1.40; 95% CI: 1.14–1.71) [3]. Also, eating too many saturated fats and having high uric acid levels have been linked to a higher risk of heart disease [4], [5]. In contrast, adopting a healthy lifestyle can reduce this risk by up to 43% [6].

The Indonesian Ministry of Health says that a random blood sugar level (RBG) is normal if it is less than 200 mg/dL, and a fasting blood sugar level (FBG) is normal if it is less than 126 mg/dL. Also, a total cholesterol level is normal if it is less than 200 mg/dL. The normal range for uric acid levels in the blood is 3.4–7.0 mg/dL for adult men, 2.4–6.0 mg/dL for adult women, and 2.0–5.5 mg/dL for children [7]. Currently, the most common way to check blood sugar, cholesterol, and uric acid levels is

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still invasive since it requires taking blood samples with a syringe. Usually, three measuring strips are needed for each test to get the values for each parameter. These tests are not only uncomfortable for patients, but they also tend to be pretty expensive. Also, the results of these tests are usually written down by hand on paper, which can cause problems like trouble finding patient information, messy recordkeeping, and the buildup of physical files, making long-term data management less efficient [8]. These limitations highlight the need for a more practical, safe, and user-friendly health monitoring system. A promising solution is non-invasive monitoring, techniques that do not involve blood sampling. Besides reducing infection risk and medical waste, this system can be enhanced with web-based electronic records accessible in real-time via smart devices.

Several previous studies have explored non-invasive approaches for monitoring health parameters. Dede [8] developed a monitoring system using the GY-MAX30100 sensor and a simple mathematical conversion to estimate blood glucose, cholesterol, and uric acid levels, achieving an accuracy of 97.13% for blood glucose and cholesterol and 89% for uric acid. However, this method did not utilize more advanced predictive statistical models, limiting its adaptability and accuracy. Subsequently, Gusti et al. [9] designed a similar system using the MAX30105 sensor combined with linear regression. This system reported an accuracy of 91.44% for blood glucose, 84.94% for cholesterol, and 84.91% for uric acid. Although linear regression offered improved accuracy over simple conversion, it remains limited in capturing the nonlinear relationships inherent in physiological data. For comparison, Jain et al. [10] demonstrated that machine learning models such as Random Forest achieved a Mean Absolute Relative Difference (MARD) of only 4.86% in non-invasive serum glucose measurement, indicating stronger performance in handling complex data patterns.

Building upon these previous studies, the present research aims to develop a non-invasive monitoring system for blood glucose, cholesterol, and uric acid levels without requiring blood sampling. The system will employ the MAX30105 sensor and processed using second-order polynomial regression to better capture nonlinear trends in physiological data, which is expected to model nonlinear data relationships more effectively than linear regression. Additionally, it will be integrated with the Adafruit IO platform for real-time data transmission and monitored through a smartphone interface built with MIT App Inventor. This approach is intended to offer a practical, safe, and efficient solution for the early detection of metabolic disorders in the community.

2. Method

This study designs and tests a non-invasive blood sugar, cholesterol, and uric acid monitoring system using quantitative methods and experimental approaches. The measurement process begins with the MAX30105 optical sensor, which detects light reflection from the fingertip. After the reflected signal is sent to the ESP32 microcontroller, it is processed using the second-order polynomial regression approach, which was chosen because it can capture the non-linear relationship between the intensity of the optical signal and the substance concentration in the blood [11], [12]. The LCD screen displays real-time information about the measurement results. Additionally, wirelessly sending data via a Wi-Fi connection to the Adafruit IO platform and a mobile application based on MIT App Inventor enables real-time access through mobile devices from multiple locations [13]. Figure 1 depicts the steps of the system's workflow, from optical signal detection to data transmission and visualization.

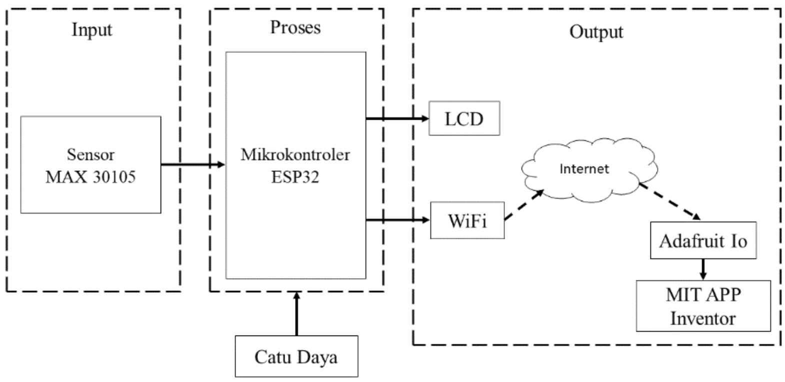


Figure 1. System Block Diagram

This system is built into a device with a rectangular acrylic case made using a 3D printing process. There is an LCD screen on top of the case that shows the measurement results right away. There is a finger clamp with a lever next to the LCD that can be changed to fit the size of the finger. This keeps the finger in the same place [14]. Figure 2 shows the whole design of the device, including how the parts are arranged and what the device will look like when it's done. Two 18650 lithium batteries connected in parallel power this device. It has a step-down voltage regulator and a USB charger module to keep the power supply stable and speed up battery charging while the device is in use.

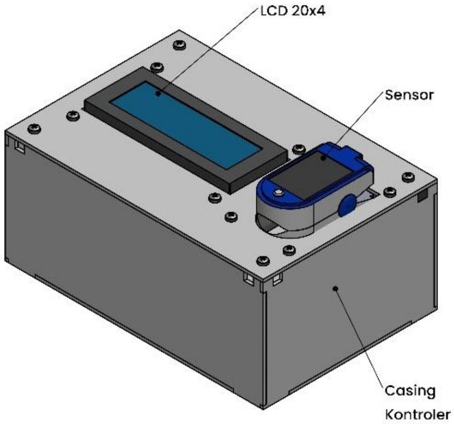
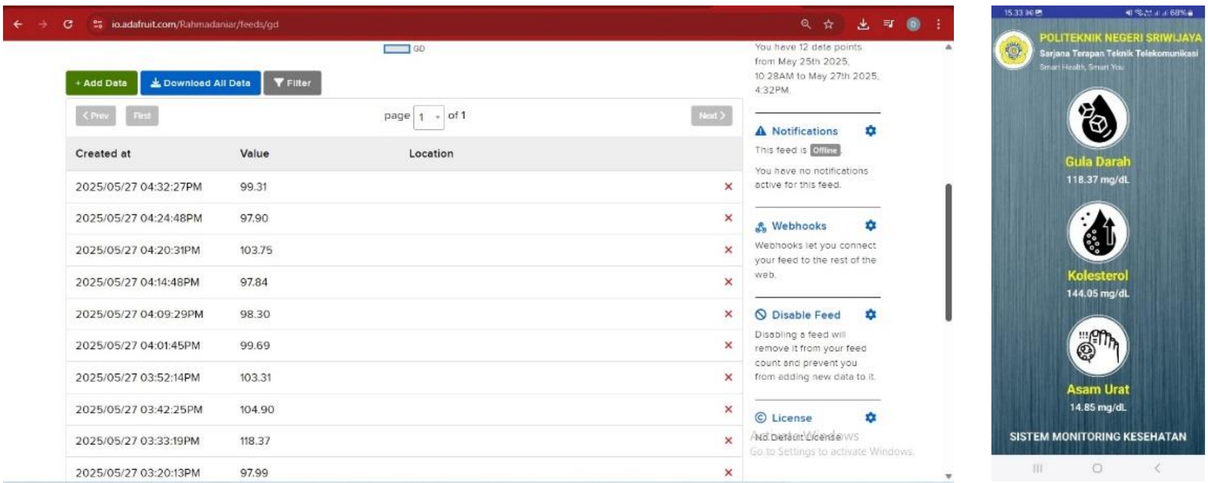


Figure 2. Design the Physical Form of the Tool

Figure 3a shows the dashboard of the Adafruit IO platform, which stores and displays biomolec data in real-time. The recorded data includes blood sugar, cholesterol, uric acid levels, and the date and time of measurement, making it easier to monitor health remotely. In addition to the dashboard, measurement results can be accessed through an application connected to the Adafruit IO platform via the Internet. This application presents the data in simple numeric values accompanied by informative animations. The application's interface is shown in Figure 3b.



A b

Figure 3. a) Adafruit IO Platform Dashboard, b) Display of Android Mobile Application Based

3. Result and Discussion

3.1 Polynomial Regression Calibration Testing

The calibration test aims to create a mathematical model that can use the reflectance measurements from a sensor that doesn't requires a blood sample to guess how many biomolecules are in the blood. The relationship between the sensor readings and the concentrations of biomolecules was not a straight line. Thus, this study used a second-order polynomial regression approach. Umar et al. [12] utilized a similar method to look at how to make a non-invasive uric acid testing device using near-

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infrared sensors. They used polynomial regression to determine how the sensor readings and uric acid levels were related [12]. The equation for the polynomial regression model is as follows:

$$y = ax^2 + bx + c \tag{1}$$

Where (x) is the sensor reading's ADC value, (y) is the estimated number of biomolecules in the blood, and a, b, and c are the regression coefficients found by training the model with reference data. The readings of the non-invasive sensors and the invasive device are compared during the calibration procedure. The independent variable (x) is the sensor measurement results, and the dependent variable (y) is the measurement results of the invasive device [15]. Based on sensor data, a mathematical model can automatically estimate biomolecule levels using the polynomial regression method. The three tests at the biomolecule level check cholesterol, blood sugar, and uric acid. Seven data samples are used in each test. The regression model's performance is evaluated using the coefficient of determination (R^2), indicating how well the model explains data variation. If two items have a high correlation, they are similar. The two things are closely connected (R^2) if approaches +1 [16]. The following regression equation was used to obtain the calibration results for the test checks blood sugar levels:

$$y \ = -6E - 08x^2 + 0{,}0099x + 82{,}787 \tag{2}$$

$$R^2 = 0{,}9816 \tag{3}$$

The $R^2 = 0{,}9816$ shows a powerful link between the sensor readings and the blood sugar levels measured by the invasive device. This means that the regression model is very reliable for use in the estimation process. Figure 4 shows a picture of the relationship.

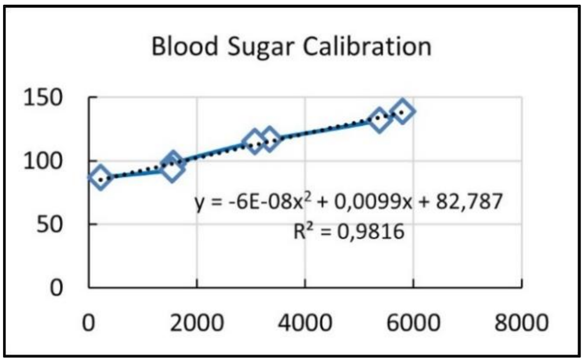

Figure 4. Polynomial Regression Graph of Blood Sugar Levels

Next, used the same sample size to test cholesterol levels and got the regression results using the following equation:

$$y = -1E - 06x^2 + 0{,}0223x + 125{,}61 \tag{4}$$

$$R^2 = 0{,}8766 \tag{5}$$

The $R^2 = 0.8766$ shows that the model fits well but not as well as blood sugar. The model remains usable for estimation but is less accurate than the previous one. Figure 5 shows a picture of the relationship.

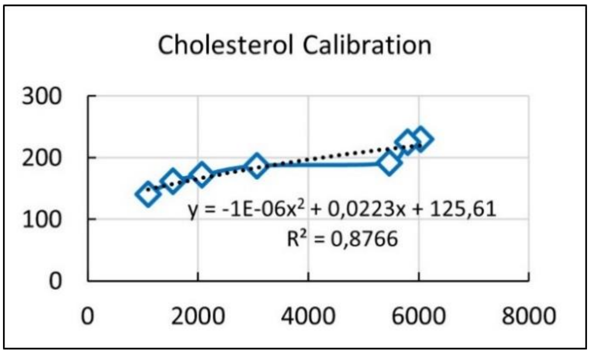

Figure 5. Polynomial Regression Graph of Cholesterol Levels

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In the meantime, the regression model for the uric acid level test is:

$$y = -5E - 08x^2 + 0,0007x + 4,5721 \quad (6)$$

$$R^2 = 0,9778 \quad (7)$$

The $R^2 = 00.9778$ shows that the model can predict things very well, almost to the point of being 1. This means that the model is very good at estimating uric acid levels without having to do anything invasive. Figure 6 shows a picture of the relationship.

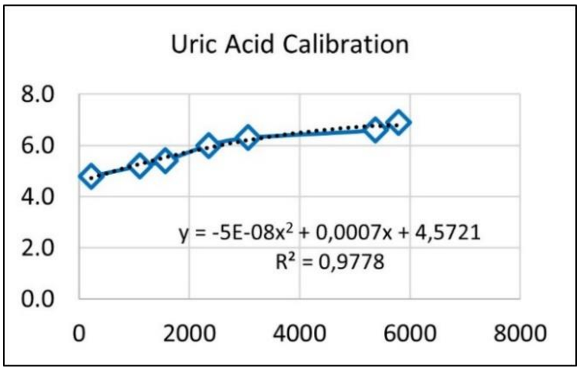

Figure 6. Polynomial Regression Graph of Uric Acid Levels

Polynomial regression in the calibration process shows that readings from non-invasive sensors are strongly and consistently related to readings from invasive instruments. The coefficient determination value obtained ($R^2 > 0,87$) shows that the regression model created is very good at explaining how data changes. As a result, this math model can automatically and accurately estimate blood sugar, cholesterol, and uric acid levels. It is also the basis for creating a non-invasive health monitoring system that uses the Internet of Things (IoT) [12], [16].

3.2 Testing Non-invasive Measuring Tools Using Invasive Reference Tools

Fifteen people were tested with this tool to see how blood sugar, cholesterol, and uric acid levels were doing. Figure 7 shows the designed tool that was used to test each participant. The results were then compared to those of a standard medical tool. After that, the data from both tools were examined to find the measurements' percentage error and accuracy.

Figure 7. Tool Testing Process

To find out how far off the measurement results of the designed tool are from those of the standard tool in percentage units, you can use the following formula to find the percentage error:

$$\%\ error = \frac{|Results\ of\ noninvasive\ measurements - Results\ of\ invasive\ measurements|}{Results\ of\ invasive\ measurements} \times 100\% \quad (8)$$

The following formula is used to figure out how accurate the tool is based on that value:

$$Accuracy = 100\% - \%\ error \quad (9)$$

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The device's performance is better when the error rate is lower, and the accuracy value is higher, making its measurements closer to those of standard medical devices. All measurement results are automatically sent to the Adafruit IO platform, which records the values and the data collection date and time. Additionally, the data is displayed through a mobile application developed using MIT App Inventor to monitor the results directly on phones. This device simultaneously tests three main health parameters that is blood sugar, cholesterol, and uric acid levels. The results from these measurements are then presented and analyzed in three separate tables (Table 1, Table 2, and Table 3) for more straightforward interpretation and comparison.

Table 1. Results of the Blood Sugar Level Test

No.	Age	R	Thickness of Skin	Results of Invasive Measurements	Results of Non-invasive Measurements	Error (%)	Accuracy (%)
1	20	59348	Normal	117	99.69	14.79	85.21
2	21	62195	Thick	140	141.81	1.29	98.71
3	21	58347	Normal	102	105.69	3.62	96.38
4	20	57549	Normal	93	97.99	5.37	94.63
5	20	61798	Thick	139	104.90	24.53	75.47
6	22	58075	Normal	119	98.30	17.39	82.61
7	21	62039	Thick	143	140.38	1.83	98.17
8	20	61372	Thick	132	103.75	21.40	78.60
9	20	59070	Normal	115	99.31	13.64	86.36
10	22	56226	Thin	87	97.90	12.53	87.47
11	20	57101	Normal	89	93.61	5.18	94.82
12	21	61467	Thick	104	103.89	0.11	99.89
13	20	59554	Normal	100	101.68	1.68	98.32
14	20	57562	Normal	98	99.29	1.32	98.68
15	21	58801	Normal	107	110.05	2.85	97.15
Average						8.50	91.50

Table 2. Results of the Cholesterol Level Test

No.	Age	R	Thickness of Skin	Results of Invasive Measurements	Results of Non-invasive Measurements	Error (%)	Accuracy (%)
1	20	59348	Normal	238	165.58	30.43	69.57
2	21	62195	Thick	276	143.60	47.97	52.03
3	21	58347	Normal	241	144.05	40.23	59.77
4	20	57549	Normal	162	157.80	2.59	97.41
5	20	61798	Thick	225	221.30	1.64	98.36
6	22	58075	Normal	172	167.60	2.56	97.44
7	21	62039	Thick	230	223.80	2.70	97.30
8	20	61372	Thick	151	142.23	5.81	94.19
9	20	59070	Normal	187	184.65	1.26	98.74
10	22	56226	Thin	224	233.74	4.35	95.65
11	20	57101	Normal	141	149.00	5.67	94.33
12	21	61467	Thick	192	217.60	13.33	86.67
13	20	59554	Normal	168	175.81	4.65	95.35
14	20	57562	Normal	190	161.41	15.05	84.95
15	21	58801	Normal	224	155.19	30.72	69.28

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Average	13.93	86.07

Table 3. Results of the Urid Acid Level Test

No.	Age	R	Thickness of Skin	Results of Invasive Measurements	Results of Non-invasive Measurements	Error (%)	Accuracy (%)
1	20	59348	Normal	6.9	6.36	7.83	92.17
2	21	62195	Thick	9.0	6.99	22.33	77.67
3	21	58347	Normal	6.0	5.94	1.00	99.00
4	20	57549	Normal	4.1	5.38	31.22	68.78
5	20	61798	Thick	6.9	6.95	0.72	99.28
6	22	58075	Normal	6.7	5.81	13.28	86.72
7	21	62039	Thick	4.6	6.03	31.09	68.91
8	20	61372	Thick	6.6	6.89	4.39	95.61
9	20	59070	Normal	6.3	6.25	0.79	99.21
10	22	56226	Thin	4.8	4.73	1.46	98.54
11	20	57101	Normal	5.2	5.30	1.54	98.46
12	21	61467	Thick	4.3	5.08	18.14	81.86
13	20	59554	Normal	4.5	5.38	19.56	80.44
14	20	57562	Normal	5.4	5.54	2.59	97.41
15	21	58801	Normal	6.4	6.14	4.06	95.94
Average						10.67	89.33

In this study, the System was tested on 15 participants to measure blood sugar, cholesterol, and uric acid levels non-invasively using the MAX30105 optical sensor combined with second-order polynomial regression. The results indicated that the accuracy of blood sugar measurements reached 91.50%, with an error rate of 8.50%. For cholesterol levels, the system achieved an accuracy of 86.07% and an error rate of 13.93%. The accuracy of uric acid measurements was 89.33%, resulting in an error rate of 10.67%. These findings show that the mathematical modeling approach to infrared optical signals can provide estimates that closely align with clinical values, particularly for self-monitoring. Although direct studies on non-invasive cholesterol and uric acid prediction using MAX30105 are limited, the applied approach follows a similar infrared optical signal modeling principle as described by Naresh et al. [17] for glucose measurement. This is consistent with the study by Naresh et al. [17], which reported high accuracy in near-infrared (NIR) glucose prediction using machine learning.

From a technical perspective, the system successfully integrated the ESP32 microcontroller with the Adafruit IO platform via a Wi-Fi connection. Data was transmitted and displayed in real time on an Android application developed using MIT App Inventor. To measure data communication performance, testing was carried out on several Quality of Service (QoS) parameters, the results of which are summarized in Table 4 below:

Table 4. Quality of Service (QoS) Test Results

Parameter	Average Value	Measurement Method
Data transmission latency	500–700 milliseconds	Stopwatch timing
Transmission Success Rate	97% (97 out of 100 data)	Serial Monitor and Adafruit IO Dashboard
Wi-Fi Signal Strength	-60 to -70dBm	MIT App Wi-Fi Signal Strength Monitor

Based on the results shown in Table 4, the transmission latency ranges from 500 to 700 milliseconds. This latency is still considered acceptable for real-time health monitoring applications, as the maximum recommended standard for health IoT services is 1000 milliseconds, according to Tagliaro et al. [18]. The success rate of data delivery reached 97%, demonstrating the system's reliability in

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maintaining the integrity of biometric data during transmission. Additionally, the Wi-Fi signal strength, which ranges from -60 to -70 dBm, ensures stable and uninterrupted data transmission to the cloud platform throughout the monitoring process.

However, data security remains a critical issue in the implementation of this system. Currently, the system has not implemented TLS/SSL encryption or authentication for the MQTT connection, making biometric data transmission vulnerable to privacy violations. This aligns with the findings of Mohammed & Alwan [19], which emphasize that using encrypted communication protocols can greatly enhance the security of IoT systems, especially in the healthcare sector. Therefore, future system development should adopt standard security protocols and authentication mechanisms to safeguard sensitive personal information. Moreover, the current system lacks historical data storage and multi-user management features, both of which are essential for clinical and community applications. It is recommended to integrate cloud services such as Firebase and ThingsBoard to support user authentication, long-term data storage, and centralized monitoring, as proposed by Roy et al. [20] and Zhang et al. [21].

In to technical issues, system accuracy is also affected by physiological and environmental factors. The thickness of the dermis and the amount of subcutaneous fat tissue can absorb more infrared light, reducing the intensity of the signal reflected and received by the sensor. Misaligned, too high, or tilted finger positions during measurement can interfere with the reflection angle and pressure, causing signal fluctuations. This finding is supported by a study by D'Souza et al. [22], which showed a negative correlation between skin thickness and PPG signal strength. In addition, interference from external lighting, such as white LEDs or sunlight, can reduce the quality of the PPG signal by up to 15%, as explained by Al-Halawani et al. [23].

Considering the overall results and evaluations, this system has shown promising technical performance for IoT-based non-invasive monitoring. However, to expand its application, it is necessary to strengthen aspects of network security, cloud-based storage systems, multi-user support, and calibration algorithms that are able to adapt to physiological and environmental variations. This development is key to improving the reliability of the system in the context of personal use and integration into digital health services more broadly. This system has the potential to become a practical and affordable stand-alone solution to support digital health services in the future.

4. Conclusion

This research has successfully created and evaluated a health monitoring tool based on IoT technology that utilizes the MAX30105 optical sensor to estimate blood sugar, cholesterol, and uric acid levels without invasive procedures. The findings demonstrate that the system has strong potential as an easy-to-use and widely accessible option for early detection of health conditions without requiring blood samples. Nevertheless, there are still various external elements that can affect the system's accuracy, including skin thickness, finger position during measurement, skin hygiene, and surrounding light conditions. These constraints emphasize the importance of enhancing the system's precision and stability. Subsequent studies should explore more sophisticated calibration techniques, incorporate sensors with greater sensitivity, and apply machine learning methods to process and interpret the collected data. In addition, testing with a more extensive and diverse group of participants is needed to confirm the system's reliability on a broader scale. If further refined, this technology could provide meaningful clinical advantages, especially in under-resourced regions. It holds promise for lowering healthcare expenses and encouraging individuals to perform regular, self-directed health assessments, which may lead to earlier diagnosis and improved disease prevention.

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